New Directions in Cognitive Educational Game Design

Ivo Bril[1], Nick Degens[2], and Eelco Braad[2]

[1]Artificial Intelligence, University of Groningen, Groningen, the Netherlands
bril.ivo@gmail.com
[2]User-Centered Design, School of Communication, Media & IT,
Hanze University of Applied Sciences, Groningen, the Netherlands
{d.m.degens, e.p.braad}@pl.hanze.nl

Abstract. What makes an educational game good? This paper describes three research directions that could provide insight in the underlying principles of effective educational games. These aspects are 1) The importance of distinguishing between types of to-be-learned knowledge, 2) the need to understand the relationship between game mechanics and learning goals, and 3) using research on intelligent tutoring systems to create more personalized learning experiences. Central in these directions is the concept of cognition and how it impacts the educational effectiveness of an educational game. This paper will give a short introduction on cognition and discuss why the research directions require further research.

Keywords: Educational Games · Cognition · Learning · Intelligent Tutoring Systems · Instructional Design

1 Introduction

The dream of educating so-called digital natives through engaging videogames was met with much skepticism at the turn of the century. A decade later, this skepticism has been replaced by a cautious optimism that educational games can have beneficial learning effects [1, 2, 3]. Instead of focusing on questions such as: “can educational games be a potential tool for educational purposes?” and “can educational games be better learning tools than traditional tools?” we now focus on the question: “what makes an effective educational game *good*?” This has led to new topics, such as how the design of educational games should be discussed [4], and which methodological aspects of educational game research are still lacking [5, 6].

This paper will focus on three research directions that still lack thorough research, but are strong contenders for understanding the underlying principles of effective educational games. These three directions are as follows.

1. The knowledge that a user acquires from playing an educational game (domain-specific knowledge) and the prior knowledge required to be able to play said game (game-specific knowledge) need to be considered separately in the design of educational games.

adfa, p. 1, 2011.

2. The relationship between different types of game mechanics and different types of learning goals needs to be formalized and better understood.
3. The applicability of Intelligent Tutoring Systems (ITS) literature on its overlapping educational game design aspects (e.g. adaptability) needs to be investigated.

These three directions have one fundamental overlap: they are based on how people learn and how their cognitive processes accommodate learning. We discuss this from a user-centered design perspective; the majority of the instructional and design choices should be based on how specific people acquire new information and skills.

We believe that underlying principles of effective educational game design can be distinguished in three categories, each interacting with the other two. These categories are 1) the user, 2) the learning content, and 3) the game [7]. This paper will look at ideas which focus mainly on the interaction between the learning content and the user, something of which we believe requires more research.

This paper will first describe the role of cognition in learning, which can be found in Chapter 2. In Chapter 3 to 5, we will discuss each of the research directions in more detail. Finally, we will discuss and conclude our work in Chapter 6.

2 The Role of Cognition in Learning

The cognitive processes that provide us with the ability to store, structure, and retrieve new information are fundamental to learning. They allow us to remember a theoretically infinite amount of knowledge, ranging from exact facts (e.g. giraffes have a long neck) to the context in which these facts are learned (a combination of smell, sound, emotions, etc.) [8]. Of particular importance in this process is 1) identifying different types of knowledge, 2) understanding how knowledge acquisition occurs for these types, and 3) formalizing how the knowledge acquisition process can be facilitated.

2.1 Types of knowledge

Knowledge is taken in, stored, and recalled in different ways. Some knowledge can be recalled explicitly (e.g. facts about a giraffe's physique), while other knowledge can only be recalled implicitly (e.g. how to ride a giraffe). This distinction can be mapped to the difference in storage systems, i.e. between declarative memory and non-declarative memory [9].

Declarative memory can be further subdivided into primary, or working, memory, semantic memory, and episodic memory [10]. Semantic memory is used to store facts, relations between those facts, and the resulting meaning of those facts. Episodic memory is used to store past experiences, including autobiographical aspects such as the time, place, feeling, and sounds associated with those experiences.

Non-declarative memory is used to store implicit knowledge about visual and auditory information, as well as implicit knowledge about doing (motor skills) and reasoning (cognitive skills). The latter pair, which describes one's skills and habits, is referred to as procedural memory [11].

Finally there is strategic knowledge: knowing when to apply a specific skill to solve a specific problem. This type of knowledge is a combination of semantic knowledge, episodic knowledge, and procedural knowledge, and it is acquired from previous experiences in which specific skills have been applied to specific problems.

2.2 Knowledge acquisition

When confronted with new information, we initially try to interpret this information within existing knowledge schemas [12]. By doing so, we give more relevance to what is to be learned, i.e. we embed it in what we already know [13]. Another benefit of this process is that it supports recall at a later moment; the more connections we can make to existing knowledge, the easier it is to remember the information [14]. Properly learning a skill or procedure may even require prior task-related semantic knowledge, as that may be needed to understand the steps taken in the procedure itself [15].

Initially, recalling and executing a procedure, or skill, requires conscious processing, which may impose a severe cognitive load on the learner [16]. However, the more one uses the skill, the more 'ingrained' the skill becomes, decreasing the cognitive load required to recall the steps of which it consists.

This process is very visible when learning how to drive a car; at first, you have to understand all the different skills involved: steering, switching gears, balancing gas and breaks, etc. Managing all these skills the first time you are driving will demand all of your focus, making it difficult to be fully aware of what is happening around you, let alone chat with your instructor. However, the more experienced you get at driving, the less cognitively demanding the aforementioned skills become (i.e. you become *fluent* in those skills). In turn, this allows you to focus on the traffic around you, anticipate possibly dangerous situations, and perhaps chat with your instructor.

This *fluency* allows the learner to acquire strategic knowledge. The reason fluency often supersedes strategic knowledge is in the fact that the learner's cognitive abilities are less taxed when fluency has been achieved, allowing the learner to think more about *when* and *why* a specific skill may solve a specific problem. The lack of strategic knowledge is what best defines the difference between experts and novices, as experts are able to recognize a problem's patterns, while novices still have difficulty grasping the problem as a whole [17].

2.3 Facilitating knowledge acquisition

The way in which a student is instructed and assessed influences the way his or her knowledge is structured and the effectiveness with which information is being learned. The work in [18] provides a set of five guidelines which reflect a contemporary view on effective instructional design for educational games:

- *"Stimulate semantic knowledge*.
  Relate material to the learner's experiences and existing semantic knowledge structures to facilitate learning and recall of the information.

- *Manage the learner's cognitive load*.
  Organize material into small chunks, and build up gradually from simple to complex concepts.
- *Immerse the learner in problem-centered activities*.
  Provide opportunities for learners to work immediately on meaningful, realistic tasks.
- *Emphasize interactive experiences*.
  Develop problem-centered activities that require manipulation of objects to encourage active construction/processing of training material to help build lasting memories and deepen understanding.
- *Engage the learner*.
  Devise learning scenarios that maintain the performance of learners in a "narrow zone" between too easy and too difficult." [18]

As can be seen from their descriptions, many of these educational principles are related to how we acquire, process, store, and retrieve knowledge of different types. These aspects therefore need to play an important part in designing educational games with learning goals in the cognitive domain.

3 Distinguishing learning and play

In order to be able to learn from a specific tool or medium, the learner should already know how to use it. For example, when one is expected to learn for an exam by reading the prescribed book for a course, one has to be able to extract the knowledge from the medium (i.e. written text). Not knowing how to read, lacking proficiency in the written language, or simply having difficulties understanding the writing style are all aspects that can interfere with the learning process.

In educational games, the medium is an interactive environment in which the learner is supposed to interact with the environment to acquire knowledge and learn skills. The same problem from the example above applies in this situation, albeit in a different way: not knowing how to navigate in a 3D environment, not knowing how to progress through the learning environment, and not being able to distinguish relevant knowledge from irrelevant knowledge may all impact the effectiveness of the educational game.

This is also found in previous research, showing that users with prior general gameplay experience learned more from an intervention then their less experienced peers [19, 20]. Furthermore, from observing and interviewing the non-experienced users, it became clear that they had difficulty focusing on the domain-specific knowledge, as they were too busy figuring out how to interact with the game.

From the cognitive principles described in Section 2.3, we can see game play as an extraneous cognitive load caused by the fact that the tool itself requires cognitive effort to use [21]. Thus it is crucial as a designer to take this into account and consider both the game play and the domain knowledge as separate learning goals. Of course, the basics of the game play would have to be taught prior to introducing the domain knowledge or else the user would not know how to play at all. Designers are tasked with not only with creating engaging experiences as part of the game play, but also have to keep an eye on the balance between the user's game play expertise and domain knowledge expertise. This can be seen as an extension to the guideline "*Manage the learner's cognitive load*", as described in [18].

4 The relationship between learning goals and game mechanics

The idea of having the game mechanics and the learning goals be seamlessly integrated into an educational game is far from new. Empirical research shows that this approach is effective in terms of motivation and learning effectiveness (e.g. [22, 23]). However, less is known about how the choice in game mechanics in and of itself can influence learning.

4.1 SURGE: learning Newton's second rule of motion

An interesting example of the impact of game mechanics on learning was found in [24], in which students learned more about Newton's second law of motion by controlling a space ship through a 2D environment. The user could change velocity in four directions: up, down, left, and right. For example, a ship moving to the right could be slowed down by applying power in the opposite direction. While the game was engaging, and positive learning results were found, the most interesting result was that the students had learned the principles *implicitly*. They could not explain their reasoning for the answers they gave on the physics test, even when they gave the correct answer. The authors argued that this was due to the fact that the game did not promote (cognitive) formalization of the concepts used in the game.

Important to note here is the fact that the game play was real-time, and mostly reaction-based; the user had to react to obstacles that appeared on the screen in a timely fashion as the user progressed through the level. While this does require the user to become familiar with the controls, and in extension the way the second law of motion works, there was no need for the user to reason about how the controls worked.

4.2 Fuzzy Chronicles: the follow-up to SURGE

In [25], the authors of the previous game created a follow-up game that would teach all of Newton's laws of motion. Here the goal of the paper was different: determining the influence of self-explanation questions and explanatory feedback. However, the game used a different set of mechanics than in the previous game: instead of real-time navigation, the user has to select a set of a-priori actions that are executed sequentially after the user decides to 'start the level'. The aim of the game is to ensure that the set of actions direct the ship from a start point to an end point.

This setup requires the user to play the game differently than SURGE, as the problem had to be reasoned about beforehand as opposed to reacting in real-time to changing situations. The students had a more explicit understanding of the laws of motion than in researchers' previous work on SURGE.

4.3 What does it mean?

Both games help us to identify that the style of game play, i.e. the mechanics, will influence the learning process. From a cognitive perspective, Fuzzy Chronicles allowed the user to process and deal with specific problems without the extraneous load of navigating a space ship in real-time to avoid collisions. Related follow-up questions to these papers are: does real-time input lead to better results with regards to behavioral learning? Do strategic puzzle-like mechanics lead to better results with regards to promoting knowledge structuring?

The only way to answer these questions is by understanding the cognitive process of information and skill acquisition and understanding how different mechanics relate to instructional and cognitive theories.

5 Applying ITS literature to educational game design

The design goal for educational games is to provide an optimal learning environment; a goal shared by the design of Intelligent Tutoring Systems (ITS). Still, there are differences. The field of intelligent tutoring systems has progressed much in for example implicit and online assessment [28] and has even worked on including game-like aspects such as narrative [31, 32]. On the other side, educational game design research has not had the same progression with regards to assessment and feedback [30], and has not incorporated many other results from ITS-studies. It is therefore useful to consider these results and possibly apply them to educational game design.

The following sections will explain what an ITS is, how it is able to provide such adaptive support, and it will conclude with the state of educational game design with regards to user modeling and adaptability.

5.1 What is an Intelligent Tutoring System?

Whereas educational games aim to engage and motivate users, ITSs aim to provide optimal support throughout the learning experience by closely simulating a personalized tutor. An example of well-developed ITS' are the *Cognitive tutors* which have been used to teach mathematics to students in the United States for over two decades now [26].

The level of detail with which these tutors can monitor the student's learning process allows them to select the right kind of feedback and the most relevant questions to increase the effectiveness of a learning session [27]. The main reason that ITSs are able to provide such a fine-grained learning experience is their usage of principles of cognitive theory, aided by methods of artificial intelligence to learn from the input of the learner [28].

This process requires a more formal representation of knowledge and the cognitive processes involved in acquiring that knowledge. Cognitive architectures such as ACT-R allow this formalization and help to describe a student's level of understanding in the computational terms, leading to models of student competency [29].

5.2 How do ITS' formalize knowledge and use it?

Cognitive architectures such as ACT-R allow tutoring systems to decompose otherwise complex tasks into 'procedures'. These procedures consist of a chain of 'production rules', which are simple if-then clauses. When a math problem (e.g. 8+3) requires the addition procedure, the if-then clauses range from "if the left and right arguments are positive, add them together" to "if the sum of both arguments' ones exceed ten, remember to add one to the tens". These production rules consist of a combination of procedural knowledge and declarative knowledge. Each of these production rules has a certain probability of recall, which is determined by how often the rule is used. Less use means a smaller chance of recall [26].

A tutoring system not only keeps track of the production rules a user needs to know, but also the user's probability of recall for each rule. The system does this by modeling the cognitive process of memory decay and rehearsal effects, which give a rough estimate of the probability of recall. Aside from production rules and their recall probabilities, the procedures which consist of these rules are also tracked and evaluated [26].

The combined power of both the proficiency of the user on the procedures and the user's knowledge of the production rules allows the ITS to ask questions which train the user's 'weakest' procedures and thus stimulate recall of almost forgotten production rules.

5.3 The state of user modeling in educational game design

The fine-grained tracking of a student's knowledge seems to have only gained traction over the past six years [33, 34, and 35]. In those years, the results of research on evidence-centered design (ECD) show promise of a good approach to formulate and assess a student's competencies with regards to the learning goals of a game [36, 37]. ECD consist of three important steps: providing a competency model (what has to be assessed?), an evidence model (what kind of behavior has to be elicited for effective assessment?), and a task model (how can we elicit that behavior?).

ECD has the possibility of bypassing one of the barriers preventing the use of ITS literature in educational game design: the strictness of cognitive architectures. While the formal approach to knowledge found in architectures such as ACT-R allows an ITS to keep track of the student's progress, to a high level of detail, it also requires the to-be-learned skills to be formulated in production rules (as such is the language of ACT-R). The more flexible approach provided by ECD allows the designer to formalize the knowledge less strictly.

5.4 Using user models in educational game design

Educational game design shows promising results in assessing the user and using this knowledge for adaptive game play (e.g. scaffolding instructional content) is the next logical step [37]. ITS research could be used as basis for this step; providing tailor-made feedback and challenges are two key features of such systems [38]. A lot of developments, such as finding the right methods for statistically inferring the right feedback or questions, have already taken place in the field of ITS [39, 40]. As a first step the field of educational game design could look at the following problems already discussed in ITS literature:

1. Look into the use of artificial intelligence, not only for determining proficiency probabilities (as is done in [37]), but also for determining the right feedback and challenges [e.g. 40, 41].
2. Look into measures of adaptivity and the ongoing discussions in the field of ITS on how an educational game should adapt to its user [42].

6 Discussion and Conclusions

In this paper we have identified and described three research directions that will help the scientific community to build more effective educational games (and included relevant and recent articles looking into these directions). This is in line with previous work in which we formalized three dimensions of effective educational games [7]; the research directions represent important aspects that are required to bridge the gap between 'the users and their learning process' and the gap between 'the game mechanics and the learning process'.

The first direction emphasizes the need to differentiate between 'learning how to play the game' and 'achieving the intended learning goals'. Not taking this into account may lead to lower learner performance and motivation throughout and after playing the game. One way to solve this is by adding tutorials or scaffolded feedback regarding the gameplay for less experienced users, but this may be off-putting to more experienced users.

The second direction emphasizes the need to understand the relationship between game mechanics and learning goals. It may be that different types of mechanics lead to a lower or higher performance for certain types of learning goals. This is very clear with regards to the relationship between 'time to input actions' and stimulating higher-order cognitive functions; if a user has to play a very reactive game, for instance a shooter, it may be difficult for users to reflect on their actions in a cognitive manner.

The third direction emphasizes the need for educational game design to further incorporate aspects and methods of intelligent tutor systems. In particular, it is becoming increasingly important to determine and apply a singular method to 1) identify domain-related competencies and how they can be inferred from user actions, 2) make sure that the game consists of activities that elicit the intended user actions, 3) create appropriate user models that help to track the user's progress through these activities, and 4) use these models to adapt both the learning content and the feedback to specific users.

These three research directions require a better formalization of the mechanics that are present in a game, the process through which different users acquire domain-related knowledge & gameplay-specific knowledge, and the optimal relationship between these two. This formalization should also help us to better describe the content of educational games; usually it is very difficult to get a good understanding of the in-game activities of an educational game and their educational quality just from their sometimes superficial descriptions.

Furthermore, for the field to mature, we need to include a certain level of adaptability in educational games to ensure that the game is a better 'fit'. By adapting the game play content and in-game feedback to the a-priori knowledge and interests of the user, as well as the learning styles of the game's target audience (e.g. children or adults), we will be able to create more effective and motivational learning tools.

7 References

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